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Synopsis for Registration as Research Student

For

Doctoral Degree

On
BRAIN COMPUTER INTERFACE USING EEG SIGNAL

By

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BRAIN COMPUTER INTERFACE USING EEG SIGNAL

ABSTRACT

The physically disabled patients with all brain functionalities are incapable of making motor response. Using brain computer interface (BCI) we can capture the motor response of brain and execute it. This is called Brain Computer interface. The aim of BCI is to interpret brain activity in the form of signal which acts as a command for a computer. One key challenge in current BCI research is how to extract features of random time-varying EEG signals and its classification as accurately as possible. Feature extraction techniques are used to extract the features which represent a unique property obtained from pattern of brain signal. Earlier EEG analysis was restricted to visual inspection only. The visual inspection of the signal is very subjective and hardly allows any standardization or statistical analysis. Hence, several different techniques were intended in order to quantify the information of the brain signal. Many linear and non-linear methods for feature extraction exist.

The main focus is on developing a system which makes the use of available EEG device, and forming a prototype that put together all parts of a functioning BCI system. These parts are 1) acquisition of the EEG signal 2) processing and classifying the EEG signal and 3) by using the signal classification control features in BCI. This work will outline the implementation of modules and testing for this system. After final implementation and testing complete system it can be used to control the outer real world with maximum accuracy.

1. Introduction

A physician Richard caton (1842-1926) knows as pioneer of EEG. He performed experiments (1987) on cats, rabbits and monkeys. He found that there are fluctuations in potentials in them that constitute the EEG. However, the first pictorial practical of EEG was performed by Vladimir Pravdich-Neminsky. He measured the electrical activity in brains of dogs and called it as *electrocerebrogram*. While doing research on brains of animals other scientists like Hans Beger (1873-1941) a neuropsychiatries, try to done it on human brain. In 1920 he

started analysis of human EEG. The first human EEG was traced in 1929 in his report on EEG of human.

Electroencephalography (EEG) is the upcoming technology in coming down the pike years for diagnosis of Brain. All functioning of advantage is free to each distinct including Brain. Electroencephalography (EEG) is the recoding of electrical activity right to neurons in know-it-all along the scalp. The ride of current because of firing of neurons in the brain generates the voltage fluctuations that measured as EEG. The measurement of the brain's response to stimulus is called Event Related Potential (ERP). It may be because of motor, sensory or cognitive in nature.

The overarching control system for such a response, and for the selection of stimuli to which any response is to be made, is the faculty of attention. This faculty is used especially in the early stages of response, before any over-learning occurs (leading to automatic responses), so plays a most crucial role in ensuring efficiency and survivability. Thus we consider that in order to understand emotions it is necessary to build models of how emotions guide attention itself. It is that logic that has caused us to investigate the interaction between attention and emotion. Attention is a faculty of many animal species, used to reduce the flow of information into the sensory system of the brain by enhancing the relevant or important components of the input stream while eliminating the distracting ones. This operation is guided by the goals, sited mainly in the prefrontal cortex, that maintain the template for these relevant or important components. What determines the relevance or importance of incoming stimuli according to which attention is applied and actions in response to the attended stimuli are generated?

After the discovery of more brain technology like MRI, fMRI, CT scans etc. the diagnosis of brain related diseases become easier. Problems related brain like Epilepsy increasing day by day. EEG is best tool for such problems. The EEG gives a coarse view of neural activity and has been used to non-invasively study the physiology of the brain. EEG activity is quite small signal, measured in microvolt (μV) with the main frequencies of interest up to approximately 30 Hertz (Hz). There are fixed frequency bands in EEG which are as follow,

The EEG keeps record of the electrical activity of the brain. The different brain wave activities identify the specific stage of brain and body. Correct EEG electrode placement is

important to ensure proper location of electrodes in relation to cortical areas so that they can be reliably and precisely maintained from individual to individual. There are generally two methods of placing electrodes on scalp. a) 10-20 international system: 21 electrodes b) 10-10 international system: 64 electrodes. The EEG analysis is important in many aspects like medical and non-medical fields. It can be done as follow.

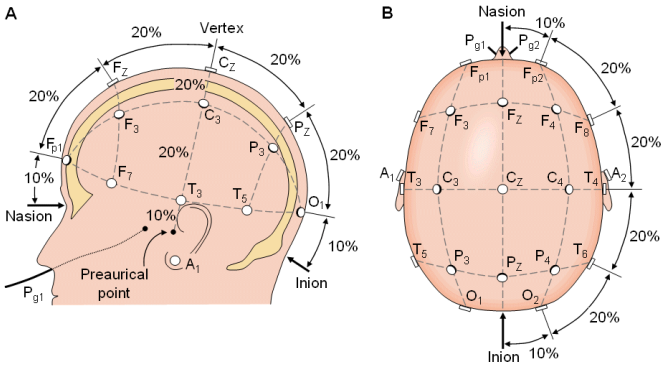

Fig1. 10-20 international system

The EEG reports contain of a number of different sections. The recordist may prepare a report describing the type of activity seen in the record together with changes produced by deep breathing and photic stimulation. They will also comment on the patient's state during the recording. The physician will then interpret these changes with regard to the medical problem being investigated.

2. Literature Survey

In the past 15 years, many research groups have explored the possibility of establishing a direct (no muscular) communication channel between the brain and the external world, by interpreting brain signals, such as neural spikes and cortical and scalp EEGs, in an online fashion. This communication channel is now widely known as the brain–computer interface.

Various discrete categorizations of emotions have been proposed, such as the six basic emotions proposed by Ekman et al. [2] and the tree structure of emotions proposed by Parrott [3]. Dimensional scales of emotion have also been proposed, such as Plutchik's emotion wheel [4] and the valence-arousal scale by Russell [5]. With tens of years of exploration of motor cortex function on primates, several neurophysiology groups have been able to teach a monkey to control a computer cursor and robotic arms by using its neuron activities [4–7]. An extensive

review of affective audiovisual databases can be found in [5] and [6]. Lisetti and Nasoz [7] used physiological responses to recognize emotions in response to movie scenes. Yazdani et al. [9] proposed using a brain-computer interface (BCI) based on P300 evoked potentials to emotionally tag videos with one of the six Ekman basic emotions. Wang and Cheong [10] used audio and video features to classify basic emotions elicited by movie scenes. There are also various studies on music affective characterization from acoustic features [10-12].

Research regarding EEG signals, concentration, and learning remains immature because scholars and researchers have only recently begun exploring this field. A further motivation for such research is to facilitate long-distance learning [13, 14]. Because actual face-to-face contact between teachers and students is impossible with long-distance learning, the difficulty of assessing students' learning state is greater than that with the face-to-face teaching method. Therefore, scholars and researchers have begun examining the relationship between EEG signals, learning, and concentration. In 2001, Gerlic *et al.* [15] observed alpha activity to examine the differences in EEG signals generated by beginner teachers compared to professional teachers, and by teaching courses that employ textual materials compared to multimedia materials. The results showed that learning ability is better controlled under the instruction of professional teachers, and multimedia material more easily stimulates brain activity compared to textual material. Yaomanee *et al.* [16] identified locations on the scalp that are suitable for detecting attention related EEG signals. The study involved three experiments (*i.e.*, reading a book, locating 3D figures, and answering questionnaires) for determining whether the subjects were attentive.

Sander Koelstra [18] presents a multimodal data set for the analysis of human affective states and Mohammad Soleymani [19] presents a user-independent emotion recognition method with the goal of recovering affective tags for videos using electroencephalogram (EEG), pupillary response and gaze distance. Feature Extraction and Selection for Emotion Recognition from EEG in time domain, frequency domain and time-frequency domain for each channel computed [20].

3. Objectives of Research

a. To investigate and predict behaviorally induced changes or "cognitive states" in a user's brain signals.
b. To develop novel features extraction for representing primary emotions and how it leads to categorical Brain Computer Interface for education, self-regulation, security as well as games and entertainment.
c. To find microstates in cognitive and emotional tasks.
d. The progress and realization of practical applications depends on systematic evaluations and comparisons of different brain signals, recording methods, processing algorithms, output formats, and operating protocols.

4. Methodology to be adopted:

Subjects

We will study some healthy subjects. Subjects will be recruited through advertisement in college. Exclusion criteria included a self-reported medical illness and history of drug or alcohol abuse. Written informed consent will be obtained from all participants and the protocol is approved by the local ethics committee at the college.

EEG Recording

Data used in this study will be collected as part of a baseline assessment in a larger research study investigating the effect of non-invasive brain stimulation on various cortical processes. Subjects were instructed to sit in a comfortable armchair. **Enobio® is a wearable, wireless electrophysiology sensor system for the recording of EEG**. Using the superb Neuroelectric Cap, **Enobio 32 is ideal for high-density recording research applications**. It comes integrated with an intuitive, powerful user interface for easy configuration, recording and visualization of 24 bit EEG data at 500 S/s, including Spectrogram and 3D visualization in real time of spectral features.

EEG Preprocessing

Data were imported into MATLAB for preprocessing. The open source signal processing functions available through the EEGLAB toolbox version 16b were used for data import and preprocessing. The EEG waveforms were epoched into segments of 2 second duration and down sampled to 2 kHz. A notch filter (band-stop: 55–65 Hz) was used to remove the 60 Hz noise.

EEG signals were band passed filtered for the frequency range of 1–50 Hz to further minimize contamination by high frequency artifact.

Signal Processing

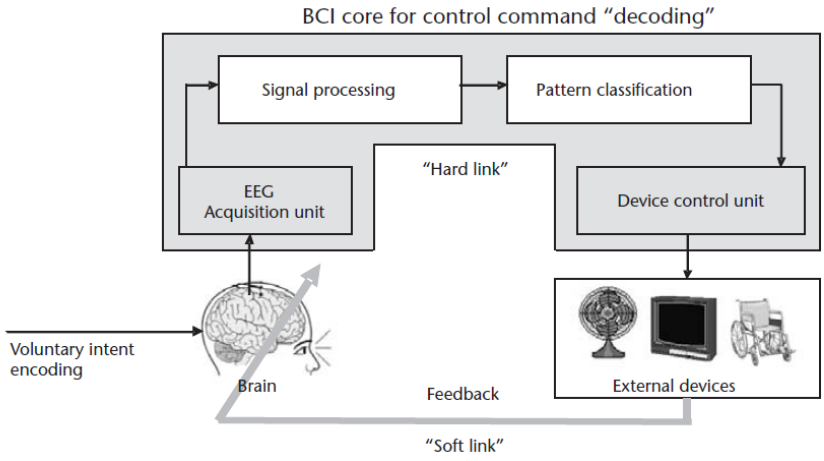

Fig 3 Block diagram of BCI using EEG

A BCI measures brain signals and processes them in real time to detect certain patterns that reflect the user's intent. This signal processing can have three stages: preprocessing, feature extraction, and detection and classification.

Preprocessing aims at simplifying subsequent processing operations without losing relevant information. An important goal of preprocessing is to improve signal quality by improving the so-called signal-to-noise ratio (SNR). A bad or small SNR means that the brain patterns are buried in the rest of the signal (e.g. background EEG), which makes relevant patterns hard to detect. A good or large SNR, on the other hand, simplifies the BCI's detection and classification task. Transformations combined with filtering techniques are often employed during preprocessing in a BCI. Scientists use these techniques to transform the signals so unwanted signal components can be eliminated or at least reduced. These techniques can improve the SNR. The brain patterns used in BCIs are characterized by certain features or properties. For instance, amplitudes and frequencies are essential features of sensorimotor rhythms and SSVEPs. The firing rate of individual neurons is an important feature of invasive BCIs using intercortical recordings. The feature extraction algorithms of a BCI calculate (extract) these features. Feature

extraction can be seen as another step in preparing the signals to facilitate the subsequent and last signal processing stage, detection and classification.

Detection and classification of brain patterns is the core signal processing task in BCIs. The user elicits certain brain patterns by performing mental tasks according to mental strategies, and the BCI detects and classifies these patterns and translates them into appropriate commands for BCI applications. This detection and classification process can be simplified when the user communicates with the BCI only in well-defined time frames. Such a time frame is indicated by the BCI by visual or acoustic cues. For example, a beep informs the user that s/he could send a command during the upcoming time frame, which might last 2–6 s. During this time, the user is supposed to perform a specific mental task. The BCI tries to classify the brain signals recorded in this time frame. This type of BCI does not consider the possibility that the user does not wish to communicate anything during one of these time frames, or that s/he wants to communicate outside of a specified time frame. This mode of operation is called synchronous or cue-paced. Correspondingly, a BCI employing this mode of operation is called a synchronous BCI or a cue-paced BCI.

SSVEP-Based BCI

Visual evoked potentials (VEPs) reflect the visual information processing along the visual pathway and primary visual cortex. VEPs corresponding to low stimulus rates or rapidly repetitive stimulations are categorized as transient VEPs (TVEPs) and steady-state VEPs (SSVEPs), respectively. Ideally, a TVEP is a true transient response to a visual stimulus that does not depend on any previous trial. If the visual stimulation is repeated with intervals shorter than the duration of a TVEP, the response evoked by each stimulus will overlap each other, and thus an SSVEP is generated. The SSVEP is a response to a visual stimulus modulated at a frequency higher than 6 Hz. SSVEPs can be recorded from the scalp over the visual cortex, with maximum amplitude at the occipital region (around EEG electrode Oz). Among brain signals recorded from the scalp, VEPs may be the first kind used as a BCI control. After Vidal's pilot VEP-based BCI system in the 1970s and Sutter's VEP-based word processing program with a speed of 10 to 12 words/minute in 1992 and Gao et al. independently reported the method for using SSVEPs to determine gaze direction. Two physiological mechanisms underlie SSVEP-based BCI. The first one is the photic driving response, which is characterized by an increase in amplitude at the stimulus frequency, resulting in significant fundamental and second harmonics.

Therefore, it is possible to detect the stimulus frequency based on measurement of SSVEPw. The second one is the central magnification effect. Large areas of the visual cortex are allocated to processing the center of our field of vision, and thus the amplitude of the SSVEP increases enormously as the stimulus is moved closer to the central visual field. For these two reasons, different SSVEP patterns can be produced by gazing at one of a number of frequency-coded stimuli. This is the basic principle of an SSVEP-based BCI.

5. Importance of Study

5.1 International/National Status:

The subject of interpersonal neurobiology (IPNB) is taught in leading medical schools of the world. There are lots of journals, transitions, and conference papers on EEG and emotion. In term of numbers, about 12,897 papers are published on EEG in IEEE out of 10,786 conferences, 1959 journals and 64 books are published. An effect of research is currently as a result of carried inaccurate in verdict to derive EEG devices smaller, in a superior way portable and easier to use. So called "Wearable EEG" is based upon creating peaceful power wireless everything electronics and ‘dry’ electrodes which do not restrict a conductive gel impending used. Wearable EEG aims to provide little EEG devices which are describe only on the front and which gave a pink slip record EEG for days, weeks, or months at a lead, as ear-EEG. Such slow and easy-to-use monitoring could the way one sees it a step culmination in the diagnosis of lodged in one brain conditions such as epilepsy, and greatly refresh the end-user reception of BCI systems.

5.2 Significance of the study:

EEG is becoming increasingly important in the diagnosis and treatment of mental and brain neuro-degenerative diseases and abnormalities. The role of the EEG is to help physicians for establishing an accurate diagnosis. In neurology, a main diagnostic application of EEGs is in the case of epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study. In this chapter, we provide a brief discussion of various uses and the significance of EEGs in brain disorder diagnosis and also in brain-computer interface (BCI) systems. Brain computer interface technology represents a highly growing field of research with application systems. Its contributions in medical fields range from prevention to neuronal rehabilitation for serious injuries.

6. Year wise plan of work and targets to be achieved

Work Description	year	Cumulative Completion Percentage (%)
Literature review	2017-2018 First Year	**10**
Identification of control technique to be used		**25**
Modeling & Application of new proposed methodology	2018-2019 Second Year	**45**
Real-Time Experimentation		**65**
Debugging & Report preparation	2019-2020 Third Year	**70**
Final project report and publication		**100**

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